Probabilistic causality and decisions on bailouts of financial institutions

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Probabilistic causality and decisions on bailouts of financial institutions

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ABSTRACT

This paper uses probabilistic causality measures to support decisions about bailouts of financial institutions in non-crisis periods. The model suggested is simple and can easily be applied by practitioners. The approach is tested with daily market-based data of six large UK financial institutions. Contrary to what many experts claim, this study shows evidence that rescuing financial institutions is not always needed in order to prevent systemic crises.

Keywords: bailouts; systemic risk, systemically important institutions; probabilistic causality

JEL: G2, C49, G01

1. INTRODUCTION

The failure of a financial institution may trigger the bankruptcy of other institutions which certainly would result in national or even global economic crises. The failure of the American investment bank Lehman Brothers in 2008 illustrates this situation. Some experts suggest that this problem can be avoided if financial institutions in distress are rescued by lenders of last resort (LOLR). The first proponents to formalize this idea were Thornton(1) and Bagehot(2), according to whom, central banks (acting as LOLR) should lend as much resources as required by financial institutions in order to avoid economic crises.

However, other authors argue that the safety net provided by LOLR organizations stimulate an excessive risk-taking behavior (the so-called moral hazard) that tend to result in crises. In other words, the injection of resources from a LOLR may give bank managers and shareholders incentive to take additional risk and may reduce the incentives for creditors to monitor the financial institutions.(3,4,5)

Freixas and Parigi(6) and Freixas(7) point out that bailouts are justified only if their benefits (prevention of financial crises) outweigh their costs (stimulation of excessive risk taking in the future). Nevertheless, although these suggestions seem to be appealing, they have a downside in the sense that there would be a large degree of discretion in the LOLR's decisions. Given this challenge, the main objective of this study is to propose quantitative indicators that will help national governments and other entities acting as LOLR to quickly decide in a rational manner when the spillover risk represented by the failure of a particular financial institution is high enough to justify the bailout in spite of the potential excessive risk taken in the future. The moral hazard will be assumed to be a worthwhile side effect when the bankruptcy of a single institution would trigger a financial crisis if that institution was not supported. As stated by Stan Fischer

(First Deputy Managing Director of the International Monetary Fund, IMF), cited in Goodhart and Illing[8] (p. 24): "*Moral hazard is something to be lived with and controlled rather than fully eliminated*".

In sum, decisions on bailouts reflect the systemic importance of the financial institutions assessed. That is, a financial institution should be rescued only if its failure would negatively impact on other institutions, which means that we would face the risk of a systemic crisis.

Systemic risk measures often mentioned in the literature, such as the Marginal Expected Shortfall - MES (Acharya et al.[9]), the Conditional Value at Risk – CoVaR (Adrian and Brunnermeier[10]) and the CoRisk (Chan-Lau et al.[11]), are *associative* measures and do not allow us to draw conclusions on causality. When relying on these approaches, all we can say is whether or not the failure of institutions, say Banks A and B, tend to occur simultaneously. If they do, it is possible that there is a common cause for the bankruptcy of A and B which means that if a LOLR rescues one of the institutions this will not prevent the failure of the other one.

Danielsson et al.[12] emphasize that regulators should know whether or not a financial institution represents a risk to other institutions and simply associations do not allow us to conclude if an initial failure will spill over into other institutions.

In this context, we develop an approach based on probabilistic causality theory with a view to evaluating the potential impact of the failure of financial institutions on other financial institutions. Our main academic contribution is to propose a systemic risk measure method focused on a causality technique rather than on an associative one. In practical terms, we also contribute to LOLRs' analysts in charge of assessing the appropriateness of bailouts.

We test our method by using daily stock return data of six large UK financial institutions. Our findings indicate that, although bailouts of large institutions are typically recommended, on some occasions the bankruptcy of institutions in our sample would not have negative immediate effect on other institutions. This is an important piece of information to LOLRs because it suggests that, in those cases, bailing out distressed institutions would feed moral hazard in the banking sector without any benefit in terms of avoiding financial crises.

The remaining of this paper is organized as follows: in Section 2, we present the method used and the approach suggested. The data used in our empirical analyses is described in Section 3. Our results are presented in Section 4. Section 5 concludes.

2. METHOD

2.1. Probabilistic causality

The notion of probability is implicit in causality statements. For instance, it is commonly said that smoking causes lung cancer but it does not mean that all smokers will develop that type of malignancy. Even if we say that an icy road is the cause of a particular car accident, many cars pass over the same spot and are not involved in any mishap (Salmon[13], Chapter 14). Therefore, these statements are not deterministic; they only imply the fact that some situations or events (e.g. smoking) tend to increase the chances of something else happening (e.g. lung cancer).

The foundations of the theory of probabilistic causality were provided by Good[14,15] and Suppes[16]. A number of improvements have been proposed (see especially Eells[17]) but the key idea remains the same: causes raise the probabilities of their effects.

For consistent, we present the theory by using the notation that will be used ahead in the analysis of contagion across financial institutions. An event A is causally relevant to an event B if there is at least one condition M in some background context such that $P(A|B,M) > P(A|\neg B,M)$, where $\neg B$ indicates the non-occurrence of B (see, e.g. Eells[17] and Pearl[18], p. 250). In other words, B is causally relevant to A if the probability of A happening conditional (represented by the symbol "|") on the presence of B and M is higher than the probability of A happening conditional on the absence of B and the presence of M. Including M as a conditioning term on both sides of the expression above guarantees a constant background scenario (in theory, all the other factors that might impact on A) that holds fixed the presence or absence of confounding factors. This allows us to focus on the specific effect of B on A.

2.2. Chain rule for conditional probability

The probability of *n* joint events $A_1,\ldots,A_n$ can be expressed as: [19]

$$P(A_1,\ldots,A_n) = P(A_1).P(A_2|A_1)\ \ldots\ P(A_1|A_{n-1},\ldots,A_1)$$

where P(.) is the probability of an event and | means "conditional on". So, the probability of the occurrence of an event conditional on other events can be expressed as:

$$P(A_n \mid A_{n-1},\ldots,A_1) = \frac{P(A_1,\ldots, A_n)}{P(A_1)P(A_2 \mid A_1)\ldots P(A_{n-1} \mid A_1,\ldots A_{n-2})} = \frac{P(A_1,\ldots, A_n)}{P(A_1,\ldots, A_{n-1})}$$

For three events (which will be the structure of the approach suggested in Section 2.3), using the notation introduced in Section 2.1, we have:

$$P(A \mid B, M) = \frac{P(A, B, M)}{P(B)P(M \mid B)} = \frac{P(A, B, M)}{P(B, M)} \tag{1}$$

2.3. An approach to support bailout decisions

We apply the probabilistic causality theory to provide bailout evaluators with evidence about the impact of the distress of a financial institution on other institutions. Systemic importance of financial institutions is the key factor to guide decisions about the pertinence of bailouts. That is, only systemically important institutions should be rescued while institutions in distress that tend not to impact on other agents should be allowed to fail. Note that, as discussed in Section 1, bailing out the latter type of institutions would encourage higher risk taking which, in turn, would result in more severe crises in the future.

We define financial distress as situations when the stock return of institutions is below the 5th percentile of their respective returns in a given period. For instance, assume that the stock return of institution A is -2.5% today. If we decide to use last year as our benchmark period, we should check if -2.5% is smaller than the 5th percentile of the distribution of A's stock returns last year. If so, A is considered to be in distress today.

The market conditions M can be represented, for example, by the main stock market index in the country analyzed. In the tests ahead, we are interested in the situations where the market is not in the distress, i.e., when M is *greater* than the 5th percentile of its distribution in a past period.

By focusing on M values above its 5th percentile (or any other percentile), we screen off the impact of B on A from scenarios when distress is caused by a common factor that simultaneously affects several or all banks. This means that this approach is more appropriate for tranquil market conditions or booms (i.e. not for downturns). In times of crises, the financial markets do not operate "as usual" and the panic created by bad news and the uncertainty simultaneously impact on many financial institutions which, in other circumstances, would not suffer any damage as a consequence of the distress of other institutions. Our results in Section 4 illustrate this point.

The use of stock returns is usual in systemic risk measures heavily cited in the literature (e.g. MES and CoVaR, mentioned in Section 1). This kind of data is available at a relatively high (daily) frequency in comparison to other types of data such as accounting data retrieved from balance sheets, which means that our results can be updated on a daily basis. This is an important feature of risk measures as the situation may change very quickly and information referring to few months or a year in the past may not represent the financial institutions' situation on the day when they require support.

Following the notation defined above and adding the subscript t to indicate the time of the realizations, bailouts are recommended if:

$$P(A_t|B_t,M_t) > P(A_t|\neg B_t,M_t) \tag{2}$$

where A_t and B_t represent the distress of institutions A and B, respectively, at time t. M_t are the market conditions at time t. That is, financial support should be granted to institution B at time t if the probability of A's distress at time t conditional on B being in distress at t and on particular market conditions M at t is higher than the probability of A being in distress at t conditional on B not being in distress at t (i.e., $\neg B_t$) and on the same particular market conditions M at t. In other words, we are checking if the presence of B (i.e. institution B's distress) raises the probability of A (i.e., institution A's distress). The conditional probabilities in (2) are estimated by means of expression (1) derived from the chain rule for conditional probability.

It is worth noting that, if there is evidence that the potential impact of B on A is not immediate, lagged data of B and M can be used.

3. DATA

We test the probabilistic causality approach suggested in Section 2.3 by considering six of the seven major UK banks and building societies assumed to have a material impact on the resilience of the UK financial system, namely Barclays, HSBC, Lloyds, The Royal Bank of Scotland (RBS), Santander UK, and Standard Chartered.. These institutions were included in the most recent stress testing of the UK banking system[1]. The other institution considered in that exercise, Nationwide Building Society, is not included in this study due to the lack of data.

We use daily stock returns from 01.01.2005 to 31.12.2015 to identify situations where financial institutions are in distress. The stock index FTSE100 is used as a proxy for market conditions. Our sample period starts in 2005 because the data for some of the banks analyzed is scarce before that year.

4. RESULTS

4.1. Baseline tests

We check the results of expression (2) for all pairs of institutions in our sample by initially using moving windows of 250 business days (around one year) immediately before the day, *t*, when we decide about the pertinence of bailouts. The first value calculated to guide bailout decisions refers to the 251st day in our sample period because the first 250 days are used to calculate the (5th) percentile that will work as the benchmark to check the condition in inequality (2). Thus, if the stock return on the 251st day is smaller than the 5th percentile of the distribution of returns from the 1st to the 250th day, the respective institution is said to be in distress on the 251st day. Next, the stock return on the 252nd day is compared to the 5th percentile of the distribution of returns from the 2nd to the 251st day, and so on until the last day in the sample period.

Each side in inequality (2) is calculated following expression (1). After simplifications, it becomes the number of days when we observe the simultaneous occurrence of the three events in

[1] See "Stress Testing the UK Banking System: Guidance for Participating Banks and Building Societies" (March 2016). The seventh institution considered in the stress testing exercise, Nationwide Building Society, is not included in our sample due to the lack of data.

the numerator divided by the number of days when we observe the simultaneous occurrence of the two events in the denominator[2].

When the condition stated in expression (2) is met, institution B should be bailed out. Table 1 shows the number of days on which the distress of an institution would cause the distress in other institutions. For the purpose of presenting our results, we adopt a conservative approach and indicate bailouts as necessary when equation (1) is not defined (i.e. normally in downturns when M is below its 5th percentile). In other words, we give institution B (the one under distress) the "benefit of the doubt". Our main objective is to challenge the idea of "too-big-to-fail" and try to avoid unnecessary bailouts that would feed increasing risk taking in the banking sector, which would make the financial system even more vulnerable to crises in the future. When we cannot show evidence against financial rescues, we assume that they are acceptable.

[Insert Table 1 here]

For example, take the intersection of the two rows "Barclays" with the column "HSBC" in Table 1. The upper row referring to bailout ("1926") means that HSBC's distress would cause (in the probabilistic sense) Barclays's distress on 1926 days in the period analyzed. On the other hand, HSBC's distress would not negatively impact Barclays on 444 days of our sample period (this number can be found in the intersection regarding the lower row). It is worth noting that, in each cell, we are evaluating the institution listed in the column title (HSBC in the aforementioned example); that is, the distress of institutions in the rows is caused by the distress of institutions in the columns. However, the pertinence of bailouts should be evaluated in relation to the cause of

[2] Both the numerator and the denominator in (1) are divided by the total number of days in the sample period, which, therefore, cancels each other out.

distress in *any* of the other institutions. Simply adding the number of days when bailouts are not recommended in a particular column does not give us the actual number of days we are looking for because Table 1 does not indicate if the days in a column are the same for all conditioned institutions (the ones in the rows) or if they are different. For example, HSBC's bailout is not recommended on 444, 444, 58, 458, and 378 days with respect to the other five institutions in our sample but we do not know which of those days are the same and which ones are different.

Therefore, institutions should be rescued if they cause (again, in the probabilistic sense) the distress of at least one of the other institutions on a particular day. These results are shown in Table 2, where we see that Barclays, Lloyds and RBS would need to be bailed out on all days considered while HSBC, Santander UK and Standard Chartered would *not* impact on any of the other institutions in the sample on 494, 153, and 163 days, respectively (which means that the LOLR should refrain from supporting those institutions on those respective days). These numbers suggest that the market perceives HSBC to be the least systemically important bank among the largest UK financial institutions. In contrast, Barclays, Lloyds and RBS are seen as the most systemically important and should be bailed out whenever they are in distress.

[Insert Table 2 here]

In order to illustrate the evolution of the days when bailouts are recommended or not, we present plots concerning evaluations of HSBC over the whole sample period. Each panel refers to a pair between HSBC and another institution. Plots of the other institutions are not shown for the sake of space but are available upon request.

The solid line refers to the probability of the other institution becoming distressed conditional on HSBC's distress and on favorable market conditions (M greater than the 5th percentile in the distribution of M's past values, showing that, in principle, there would not be any common factor responsible for the distress of HSBC and of the other institution); the dashed line represents the probability of the other institution becoming distressed conditional on HSBC's non-distress and on favorable market conditions. When the solid line is above the dashed line, HSBC's bailout is recommended.

According to Panel A, HSBC's bailouts with respect to its importance to Barclays should be granted in three main periods: from the beginning of our sample period until August 2007, between March 2010 and March 2011, and from August 2013 to October 2014. On the other hand, bailouts would not be recommended in the periods August 2007 – July 2008, January 2010 – March 2010, March 2011 – January 2012, and August 2012 – July 2013. The areas where both lines are not visible in the plot indicate unfavorable market conditions. As said above, these circumstances do not allow us to use this technique to draw conclusions on the appropriateness of bailouts but, given the absence of evidence against bailouts, we argue in favor of rescues in these cases.

To some extent, Panels B to E in Figure 1 present similar patterns, namely: three (two when Lloyds is the conditioned bank) groups of days when bailouts would be justifiable and three or four chunks when bailouts would not be recommended. This corroborates the validity of our model given that this property is more reasonable and practical than a measure that results in frequent (e.g. daily) changes between the pertinence and the inappropriateness of bailouts.

Note that decisions on bailouts cannot be made based on individual plots given that the institution under analysis may not be systemic important to another particular institution but can be relevant to other institutions. Thus, in the context of our sample, on every day, the pertinence of rescuing HSBC should be assessed by means of all the panels in Figure 1 together. This evaluation results in the numbers presented in Table 2.

[Insert Figure 1 here]

The results in 2008 and 2009 confirm that this method is not proper for analyses in critical periods such as the Global Financial Crisis in that period. Both lines (regarding HSBC's distress and non-distress) are virtually zero or not defined in Panels A to C and we cannot distinguish between them. This happens because the denominator and the numerator in expression (1) depend on situations when the market conditions M are above its 5th historical percentile. In periods of crises, those values of M tend not to be in the left tail, so it is not common to observe "high" values of M values. Therefore, the joint probability of M being greater than its 5th percentile and institutions being in distress or healthy is typically zero.

4.2. Additional tests

We test another two time windows: 125 business days (around one semester) and 65 business days (around one quarter). Tables 3 and 4 show the results concerning 125-day time windows and Tables 5 and 6 show the results for 65-day time windows.

[Insert Table 3 here]

In Table 3, the analysis of each pair of institutions reveals that, except when Barclays is the conditioned bank (first two rows), the number of days when bailouts are not recommended is larger than the number of days when conditioning institutions should be rescued. This indicates that Barclays is the most susceptible bank to failures of other institutions. In general, the ratio of non-bailouts is much higher in this second analysis than in the analysis based on 250-day time windows. Although it is not reported in Tables 1 and 3, the ratio between the number of non-bailout and bailout days is 0.43 in the former and 1.70 in the latter. That is, bailouts are considered unnecessary much more often when we take into account data from one semester before the assessment rather than one year before it.

The higher number of non-bailout days is corroborated by Table 4: in comparison to Table 2, the number of non-bailout days is much higher. Using this criterion, the systemic importance ranking changes but, as in the 250-day time window, HSBC and Standard Chartered are the least systemically important institutions (highest number of days when its rescue would not be necessary). The main difference refers to RBS, which in the previous analyses was found to be the most systemically important UK institution together with Barclays and Lloyds, is the third least risky in these tests based on 125-day time windows. Barclays remains as the most systemically important (i.e. its bailout is recommended on the largest number of days in the sample).

[Insert Table 4 here]

The results in our shortest windows (65 days), presented in Table 5, show similar ratios between the number of non-bailout and bailout days at the pair level when compared to the findings in

Table 1. As per the final decisions (Table 6), the number of non-bailout days is more homogeneous across the institutions in the sample compared to the previous analyses. The list of systemic importance, from the lowest to the highest, is Santander UK, RBS, Lloyds, Standard Chartered, HSBC and Barclays.

[Insert Tables 5 and 6 here]

The difference in most of the classifications based on different time windows may be explained by the fact that longer periods (one year, in our tests) tend to capture economic cycles that tend contribute to a stronger connection across financial institutions (and therefore a higher number of bailouts recommended), which is not evident in semester or quarter periods. The little variation regarding the number of bailouts and non-bailouts for different institutions in the evaluation based on the shortest window (65 days) indicates that short periods are not sufficient to unravel the peculiarities of particular links among institutions. For that reason, using one-year time windows appears to be the best option among the ones tested here.

5. CONCLUSIONS

To refrain from bailing out institutions whose insolvency tends to trigger generalized crises or to bail out institutions that do not represent substantial systemic risk will certainly have negative consequences to the economy (in the short or in the long run). The latest example of the former situation was the collapse of the bank Lehman Brothers in 2008 and some examples of the latter might be hidden in the several bailouts recently occurred in many countries (e.g. UK and Spain).

We contribute to solving this challenging problem by presenting a method based on probabilistic causality that can help LOLRs identify situations when bailouts are unnecessary. Our empirical analyses considering six large UK financial institutions support the pertinence of bailouts most of the time but we also indicate few days when, in principle, the failure of specific institutions would not impact on other institutions. This information contributes to the reduction of potential negative effects (moral hazard) from unconditional bailouts to all large financial institutions.

It is important to note that the method proposed here is not intended to be used alone. It should be seen as an additional tool available for decision makers. Furthermore, our suggestion is limited to periods of normal or booming market activities and it is not adequate for unfavorable scenarios such as generalized panics and financial crises. Notwithstanding, this approach is an advance in terms of providing support for LOLR decisions about the pertinence of bailouts. In principle, decisions in the context of panic remain at the discretion of LOLRs and based on their feeling of the market. This paper opens an avenue for models that aim at distinguishing the causal association among financial institutions not only in upturns but also in downturns, which is the scenario when most of the banks are more likely to be in distress. In other to do so, a number of other causality techniques should be tested and other types of data (apart from stock returns) could also be used, such as Credit Default Swap spread.

Finally, we suggest that the method proposed here be adapted to other areas that involve risk analyses and the need of causal interpretations.

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Table 1: Number of days when the distress of institutions in the rows is caused by the distress of institutions in the columns (time window: 250 days)

		Conditional on the distress of					
		Barclays	HSBC	Lloyds	RBS	Santander UK	Standard Chartered
Barclays	Distress	-	1926	1946	1823	1395	1786
	Non-distress	-	444	424	547	975	584
HSBC	Distress	1432	-	1255	1714	1073	1327
	Non-distress	938	-	1115	656	1297	1043
Lloyds	Distress	2123	1926	-	2257	1358	1681
	Non-distress	247	444	-	113	1012	689
RBS	Distress	1927	2312	2184	-	1175	1473
	Non-distress	443	58	186	-	1195	897
Santander UK	Distress	1740	1912	1526	1416	-	1842
	Non-distress	630	458	844	954	-	528
Standard Chartered	Distress	1957	1992	1675	1540	1668	-
	Non-distress	413	378	695	830	702	-

Table 2: Number of days when bailouts are recommended or not (time window: 250 days)

	Bailout	Non-bailout
Barclays	2370	0
HSBC	1876	494
Lloyds	2370	0
RBS	2370	0
Santander UK	2217	153
Standard Chartered	2207	163

Table 3: Number of days when the distress of institutions in the rows is caused by the distress of institutions in the columns (time window: 125 days)

		Conditional on the distress of					
		Barclays	HSBC	Lloyds	RBS	Santander UK	Standard Chartered
Barclays	Distress	-	1839	2167	2177	1383	1523
	Non-distress	-	901	573	563	1357	1217
HSBC	Distress	877	-	1044	825	813	832
	Non-distress	1863	-	1696	1915	1927	1908
Lloyds	Distress	1425	1044	-	1401	1037	1061
	Non-distress	1315	1696	-	1339	1703	1679
RBS	Distress	1322	825	1401	-	780	701
	Non-distress	1418	1915	1339	-	1960	2039
Santander UK	Distress	793	813	1037	780	-	1312
	Non-distress	1947	1927	1703	1960	-	1428
Standard Chartered	Distress	672	832	1061	701	1312	-
	Non-distress	2068	1908	1679	2039	1428	-

Table 4: Number of days when bailouts are recommended or not (time window: 125 days)

	Bailout	Non-bailout
Barclays	2535	205
HSBC	1526	1214
Lloyds	1810	930
RBS	1625	1115
Santander UK	1862	878
Standard Chartered	1527	1213

Table 5: Number of days when the distress of institutions in the rows is caused by the distress of institutions in the columns (time window: 65 days)

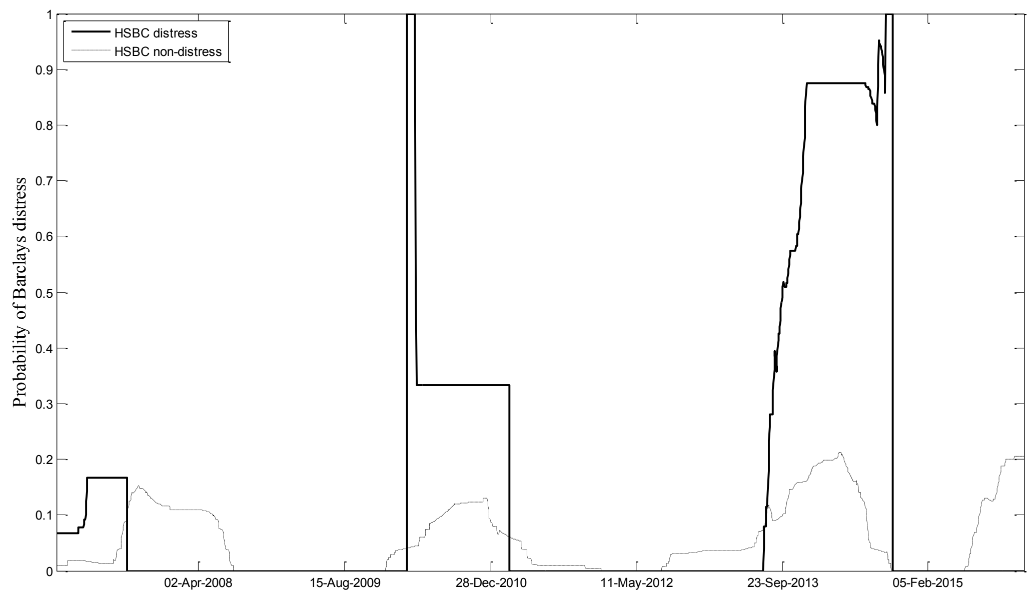
		Conditional on the distress of					
		Barclays	HSBC	Lloyds	RBS	Santander UK	Standard Chartered
Barclays	Distress	-	2206	2255	2276	2029	1689
	Non-distress	-	534	485	464	711	1051
HSBC	Distress	1973	-	1821	1704	1686	1796
	Non-distress	767	-	919	1036	1054	944
Lloyds	Distress	2161	1960	-	2309	1892	1907
	Non-distress	579	780	-	431	848	833
RBS	Distress	2058	1719	2185	-	1640	1483
	Non-distress	682	1021	555	-	1100	1257
Santander UK	Distress	1898	1788	1855	1727	-	2019
	Non-distress	842	952	885	1013	-	721
Standard Chartered	Distress	1636	1976	1948	1648	2097	-
	Non-distress	1104	764	792	1092	643	-

Table 6: Number of days when bailouts are recommended or not (time window: 65 days)

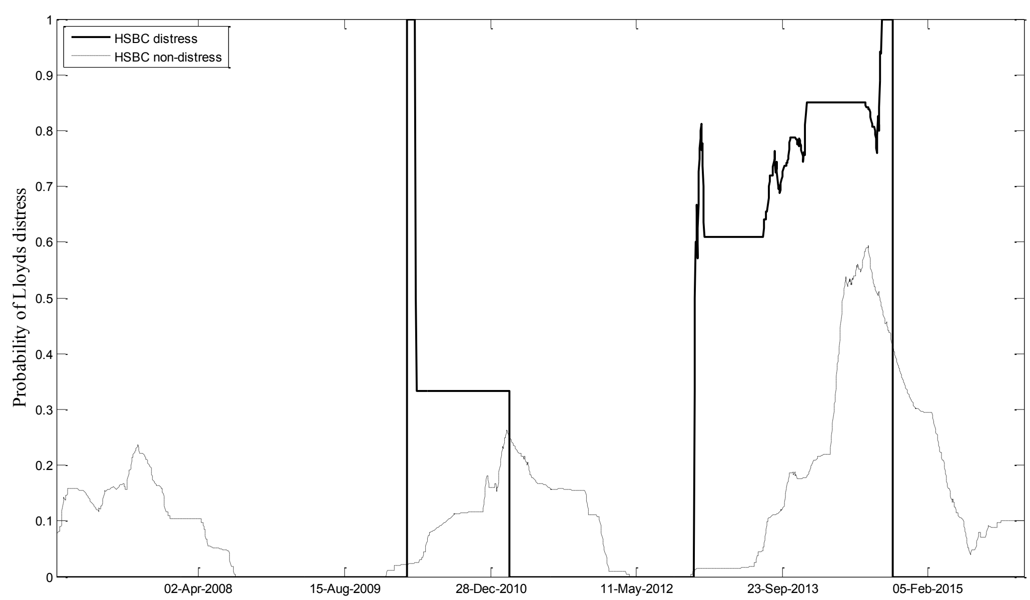
	Bailout	Non-bailout
Barclays	2689	51
HSBC	2638	102
Lloyds	2599	141
RBS	2595	145
Santander UK	2586	154
Standard Chartered	2637	103

Figure 1: Probability of distress of institutions conditional on HSBC's distress or non-distress

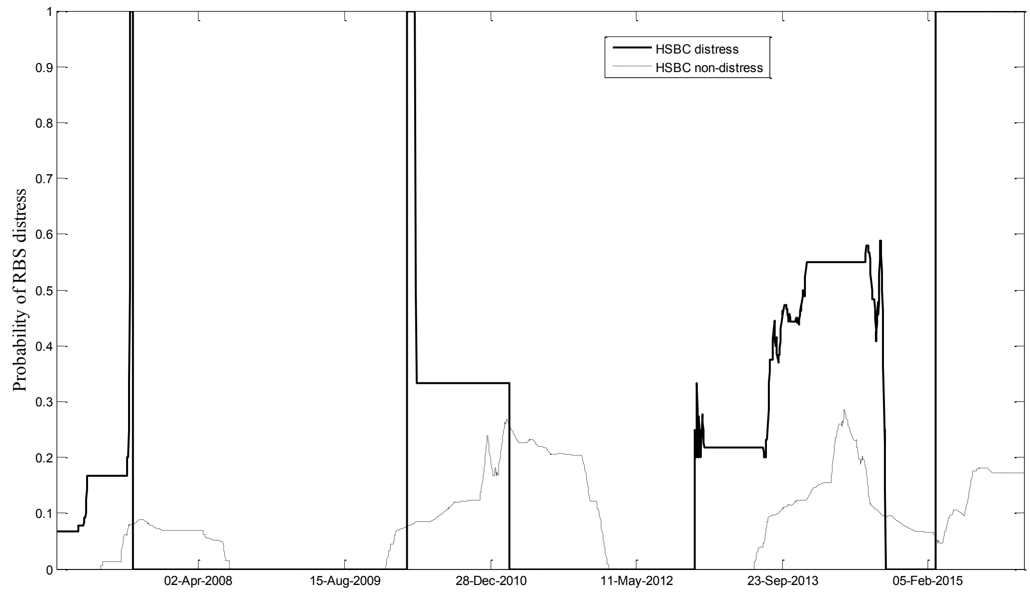
Panel A: Probability of Barclays's distress conditional on HSBC



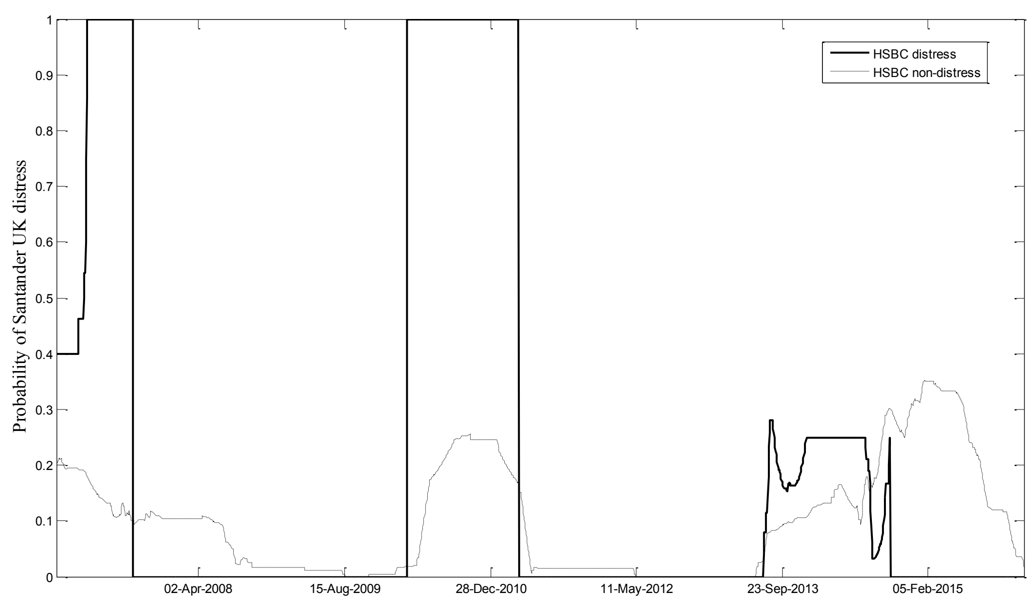
Panel B: Probability of Lloyds's distress conditional on HSBC



Panel C: Probability of RBS's distress conditional on HSBC



Panel D: Probability of Santander UK's distress conditional on HSBC



Panel E: Probability of Standard Chartered's distress conditional on HSBC